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Do gender wage differences within households influence women's empowerment and welfare? Evidence from Ghana

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ABSTRACT

Using household data from the latest wave of the Ghana Living Standards Survey, this paper utilizes machine learning techniques – IV LASSO – that allows for the treatment of unconfoundedness in the selection of observables and unobservables to examine the structural effect of gender wage differences within households on women's empowerment and welfare in Ghana. The structural parameters of the IV LASSO estimations show that a reduction in household gender wage gap significantly enhances women's empowerment. Also, a decline in household gender wage gap results meaningfully in improving household and women's welfare. Particularly, the increasing effect on women's welfare resulting from decreases in household gender wage differences is much higher than for the household welfare. The findings showcase the need to vigorously adopt policies that both increase the quantity and quality of jobs for women and address gender barriers that inhibit women from accessing these jobs opportunities in sub-Saharan Africa.

1. Introduction

The empowerment and welfare of women have become a topical issue in economic development, particularly in the developing world. For instance, because of fewer sustainable economic opportunities, women in sub-Saharan Africa (SSA) on average achieve 87% of male human development outcomes (UNDP, 2016). This generally hampers the economic and social development in the region. Over the past two decades, issues of gender equality and related development outcomes such as the empowerment and welfare of particularly women have been recognized as a major global priority. The Millennium Development Goals and now the Sustainable Development Goals (SDGs) have highlighted the importance of gender equality and empowerment of women and girls (SDG 5) and also productive employment and decent work for both men and women in order to promote inclusive and sustainable economic growth (SDG 8). The evidence from studies on women's empower-

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ment suggests that larger roles by women in decision making correlate positively with household well-being (Doss, 2006; Doepke and Tertilt, 2011; Cuberes and Teignier, 2016; Annan et al., 2020). Women's empowerment, which largely connotes the ownership and control of household productive assets and resources by women, has been found to strengthen women's bargaining position within households and communities (Desai, 2010; Doss, 2013; Meier zu Selhausen, 2016). It has therefore become important to provide more robust empirical evidence on what holds women back and what especially limits their ability to make autonomous decisions that can improve their livelihoods.

Recently, progress has been made in narrowing gender gaps in education, health, and political representation; however, these have not been matched by similar developments in labour market outcomes for women. Although there have been significant improvements in female labour force participation over the past 25 years, pervasive and persistent gender differences remain. Evidence from both developed and developing countries shows that women are paid 10–30% less than men on average for the same work (ILO, 2018). In SSA, women are significantly lagging in terms of their earning power and employment in professional and technical jobs (World Economic Forum, 2017). The gender wage gap (outside agriculture) is pervasive across all labour markets in SSA. The unadjusted gender wage gap is estimated at 30% on average. This means that, for every US$1 equivalent earned by men in manufacturing, services and trade, women earn 70 cents (UN Women, 2016). Women typically occupy the worst-paid jobs with the least protection, while attitudes towards gender frequently inhibit entry to better opportunities.

The gender wage gap may inhibit women from having equal access to economic opportunities, thereby thwarting the development outcomes for women (Galor and Weil, 1996; Lagerlöf, 2003; Blau and Kahn, 2006), whereas reductions in the gender wage gap may be beneficial to women and their families. However, gender differences in access to economic opportunities have been mostly debated in relation to gender differences in labour market participation (see World Bank, 2012). This exclusive focus on labour force participation provides only a partial picture of women's and men's experience in the labour market. Given the concerns with the gender wage gap, it is imperative to look beyond labour force participation to focus on wage differences and look at how it affects related development outcomes for women. This leads us to the question: do the pervasive gender differences in wage impose significant costs on women's welfare and empowerment?

This question has not been directly answered in the literature. Most studies have focused on how gender inequality may or may not promote economic development at the aggregate level (see Barro and Lee, 1994; Barro and Sala-i-Martin, 1995; Forbes, 2000; Seguino, 2000; Klasen, 2002; Knowles et al., 2002) whereas a few studies have looked at gender inequality, poverty, and domestic violence (Angel-Urdinola and Wodon, 2006; Aizer, 2010). It is worth noting that these studies on gender inequality and economic development draw largely from cross-country macro-level comparisons and have frequently focused on economic growth. As a result, these types of studies are less able to speak generally to the role of gender gaps in shaping household level outcomes.

The other thread of studies has distinctly focused on understanding patterns influencing women's empowerment and welfare on the one hand and gender wage gap on the other. Many of the studies on women's empowerment and welfare have focused profoundly on how microcredit affects women's empowerment and livelihoods (see Pitt et al., 2006; Kabeer, 2005; Kim et al., 2007; Garikipati, 2008; Swain and Wallentin, 2009; Rahman et al., 2017; Al-Shami et al., 2016, 2018). Some of the studies have also looked at explaining women's empowerment and welfare in agriculture (Alkire et al., 2013; Akter et al., 2017; Sell and Minot, 2018) and also how access to basic services such as electricity explains women's welfare (Winther et al., 2017). The set of papers on gender wage gaps in the literature have essentially paid attention to the extent, trends, and explanations of associated factors that drive gender wage gaps (Eastough and Miller, 2004; Ilkkaracan and Selim, 2007; Casale and Posel, 2011; Christofides et al., 2013; Langdon and Klomegah, 2013; Bhorat and Goga, 2013; Cardoso et al., 2016; Blau and Kahn, 2017; Flinn et al., 2018).

In this paper we seek to directly answer the question: do the gender differences in wage within households significantly influence women's welfare and empowerment? Here, we use the latest wave of a micro level household dataset from Ghana (Ghana Living Standards Survey 7; see Ghana Statistical Service (2018a) that contains relevant information on women's empowerment and welfare and, more importantly, on occupation and ISIC sector of work.[1] To adequately explain the dependant variables and gender wage gap, we employ a machine learning technique termed IV LASSO. The IV stands for instrumental variable whilst LASSO or Lasso represents least absolute shrinkage and selection operator. The IV LASSO treats the issue of unconfoundedness in the selection of observables and unobservables (that is, the selection of right sets of controls and instruments), an important estimation concern that fraught many studies on this subject matter (Blau and Kahn, 2000; Goldin and Katz, 2008). In this way, we contribute to the literature on how gender gaps shape a very important household level outcome—women's empowerment and welfare—in SSA where such empirical studies are prominently lacking. On the methodology front, the structural model used for this study contributes greatly to the current approaches used in the literature. The structural parameters of the IV LASSO estimations show that a reduction in the household gender wage gap significantly impacts positively on women's empowerment. Also, declines in the household gender wage gap are associated meaningfully with improvements in household and women's welfare. Particularly, the increasing effect on women's welfare resulting from a decrease in household gender wage differences is much higher than for household welfare. The findings showcase the importance of adopting policies that would increase the quantity and quality of jobs for women and also the urgent need to work assiduously on addressing gender barriers that inhibit women from accessing job opportunities.

[1] The ISIC sector of work refers to the United Nations International Standard Industrial Classification (ISIC) of all economic activities.

The rest of the paper proceeds as follows. Section 2 presents the theoretical and empirical discussions as well as the brief on the Ghanaian context. Section 3 introduces and explains how the IV LASSO methodology is applied to the analysis. The description and source of data are also contained in Section 3. A detailed discussion of the empirical results is presented in Section 4. The conclusions and policy implications of the study are inSection 5.

2. Related literature and context

2.1. Theoretical discussion: gender wage gap, women empowerment and welfare

The theoretical literature on gender wage gap has largely focused on why women on average earn less than men. Since the 1990s, economists have applied various economic theories to explain why women are denied equal wages for the same work as their male counterparts. While some economists have invoked the human capital model (*endowment effect model*) and the significantly lower level of the human capital of female workers relative to that of male workers as a potential explanation to the gender wage gap (Hossain & Tisdell, 2005), others have used labour market models and attributed a substantial part of the gender wage gap to the labour market discrimination against women (*discrimination effect*) (Ahmed and Maitra, 2010; Akter, 2005; Kapsos, 2008). According to the human capital model, the skills and abilities acquired through education, training and experience explain the variation in the gender wage gap. In this regard, Mincer and Polachek (1974) explained that women on average anticipate shorter, more interrupted and discontinuous work-life—for instance withdrawing from the labour market for a while after having children. For this reason, they tend to have a lower incentive to invest more in education and formal labour market-orientated training for improved earnings and job skills. The lower human capital investment translates into lower earnings for women relative to those of men (Becker, 1985). Even when employers have to step in to mitigate this market failure, they are reluctant to do so for the same reasons (fears of not getting a full return on investment in education and training) that discourage women to make a huge investment in their education and training. Gender roles in the family, a significant share of which is borne by women, also affect the occupational choice of women. Many at times women self-select into careers that allow for flexibility but with low-remuneration and minimal opportunity for skill upgrading to transit into high paying jobs. The human capital model has been very instrumental in explaining part of the variation in the wage disparities between women and men.

The labour market discrimination effect model on the other hand focuses on the wage inequalities between women and men that exist even when individuals belonging to both sexes have identical human capital characteristics or productive endowments but are paid differently based on their gender. In other words, the wage gap that exists even after accounting for the endowment effect (Ahmed and McGillivray, 2015). Gustafsson and Li (2000) and Ng (2007) give a hint of this when they found that in China a substantial proportion of the overall earnings gap cannot be explained by the different productivity characteristics. With backgrounds provided by Becker (1957), Phelps (1972) and Arrow (1972) and subsequent work by Oaxaca (1973), Blinder (1973), Reimers (1983), Neumark (1988) and Cotton (1988), studies in other developing countries (Akter, 2005; Kapsos, 2008) have yielded similar results. In this literature, the part of the gender earnings gap that is not explained by productivity characteristics is attributed to discrimination where even with same productivity endowment, employers may be willing to work with women in subordinate position but dislike when women occupy superior position due to patriarchic orientation and gender norms. Even with high productivity endowments, women may pull out of the labour market for a while after having children. These reasons, although not exhaustive make women less preferred and reliable choice for secured and high wage positions (Ahmed and Maitra, 2010). Over time, this creates a crowded effect where a substantial share of women are crowded into a limited number of remaining low-wage occupations (Bergmann, 1974) as women pay an economic price for seeking more flexible, less risky, and more fulfilling careers (Farell, 2005).

These theoretical postulations on gender wage gap have implications for women empowerment and welfare. However, the relationship is a priori ambiguous. Based on the model of household bargaining, pay differentials affect the status and balance of power of women to contribute to important decisions taken within the household (see (Lundberg et al., 1997; Duflo, 2003; Duflo and Udry, 2003; Rangel, 2006; Babcock, 2006). On one hand, the reduction in the gender wage gap increases women relative wage which in turn increases their bargaining power and outside options. This means that a reduction in the gender wage gap may increase women empowerment and welfare. On the other hand, women empowerment and well-being is damaged by higher gender pay gap, in terms of economic security, economic dependency and vulnerability (see Aizer, 2010; Lips, 2016).

Whiles these hypotheses are consistent with a model of household bargaining, they are inconsistent with the sociocultural models of “male backlash”. The sociocultural models of “male backlash” predict the weakening of women empowerment and the worsening of women welfare as the gender wage gap gets better (Macmillan and Gartner, 1999). According to the sociocultural models of “male backlash”, whiles a reduction in the gender wage gap might increase women empowerment, it could either reduce or increase domestic violence against women. This is because as women’s wage and empowerment increases men feel their traditional gender role may be threatened and therefore men begin to exhibit more violence when their partners become empowered (since that violates gender norms). If this is the case, women’s non-income welfare should be expected to decrease in response to a decrease in the gender wage gap. The opposite could also be true if social norms of patriarchy are weak or non-existent. However, according to Aizer (2010, 1848), ‘this sociocultural model ignores the rationality constraints faced by women in abusive relationship. That is, as their income increases, women are

more likely to end partnership if transfers decline and abuse continue'. Following the discussion above, we postulate that a higher gender wage gap could either weaken or boost women's empowerment and welfare.

2.2. Empirical discussion: gender wage gap, empowerment and welfare

As indicated earlier, many of the empirical studies have largely centred on the factors that explain the gender pay gap as well as that of empowerment and wellbeing of women. Studies on the relationship between gender wage gap and women empowerment and welfare are however lacking in the literature. In the ensuing discussion, we review some of the papers explaining gender wage gap and women empowerment and welfare and highlight the covariates used in these papers.

Several papers mainly on developed countries have examined the extent of, trends and factors that explain the gender wage gap (see Eastough and Miller, 2004; Ilkkaracan and Selim, 2007; Casale and Posel, 2011; Christofides et al., 2013; Langdon and Klomegah, 2013; Bhorat and Goga, 2013; Cardoso et al., 2016; Blau and Kahn, 2017). For instance, Eastough and Miller (2004) examined the gender wage gap for the self-employed in Australia. The authors showed that greater part of the gender wage gap in the self-employed sector may be due to liquidity constraints that are more difficult for self-employed women to overcome relative to self-employed men. Using data on gender wage gap across 26 European countries, Christofides et al. (2013) suggested that the size of the gender wage gap varies considerably across countries in definitions of the gap, and selection–correction mechanisms. The paper by Cardoso et al. (2016) investigates the mechanisms that shape the gender wage gap in Portugal. The authors show that one-fifth of the gender wage gap results from job segregation across firms. Finally, Blau and Kahn (2017) explored gender wage gap using a panel study of income dynamics microdata over the 1980–2010 period to provide new empirical evidence on the extent of and trends in the gender wage gap in the US. The authors reveal that by 2010, the conventional human capital variables explained little of the gender wage gap observed, while gender differences in occupation and industry continued to be important. The covariates used in these papers include educational attainment, job experience, demographics, occupation, industry of work, access to finance, locational dummies, job characteristics (such as full time or part time, public or private, and formal or informal), religion, parental care and gender roles, traditional ideology, ethnicity and race.

The empirical literature on women empowerment and welfare have largely focused on the role of microfinance (see Pitt et al., 2006; Kabeer, 2005; Kim et al., 2007; Garikipati, 2008; Swain and Wallentin, 2009; Rahman et al., 2017) whilst a few studies look at the importance of agriculture and access to infrastructure such as electricity on improving women empowerment and welfare (Akter et al., 2017; Winther et al., 2017; Sell and Minot, 2018). The paper by Kabeer (2005) explores the empirical evidence on the impact of microfinance with respect to poverty reduction and empowerment of poor women. The evidence shows that access to financial services does make vital contributions to the economic productivity and social well-being of poor women and their households, but it does not "automatically" empower women, unlike other interventions, such as education, political quotas, and others, that seek to bring about a radical structural transformation to empower poor women. Swain and Wallentin (2009) also examine the impact of the Self-Help Group (SHG) Bank linkage program on women's empowerment. The authors show that on average, there is a significant increase in the empowerment of women in the SHG members group. With regards to the role of agriculture, Akter et al. (2017) used data from four Asian countries: Myanmar, Thailand, Indonesia and the Philippines and highlighted the need to introduce country-specific gender intervention necessary to overcome gender gaps in agriculture. The paper by Winther et al. (2017) established that electricity access benefits the welfare of women as well as men, but that the impact on gender relations remains largely unclear. In explaining women's empowerment and welfare, these papers measure women's empowerment using the share of assets owned by women whilst the covariates include variables such as demographics and household and family characteristics social norms and culture, access to basic infrastructural services, access to finance, educational attainment, occupation, household size, household income, ethnicity, marital status, and land ownership.

The closest study that attempts to explain the link between women empowerment and welfare and gender wage gap is the paper by Aizer (2010). Aizer (2010) looks at the impact of the gender wage gap on domestic violence in the US. The findings show that a reduction in the gender wage gap is responsible for nine percent of the decline in domestic violence against women witnessed in the US between 1990 and 2003. Following from a household bargaining model, one can infer that reduction in violence against women is a strong signal of women empowerment and wellbeing.

Premised on the discussions above, our study makes a major contribution to the literature from three fronts. First is the attempt to directly examine the nexus between gender wage gap and women empowerment and welfare. As indicated, there are no studies that have been done to this effect. Secondly, the analysis is done at the household level and in a developing country—Ghana—where studies are also lacking. Thirdly, the high dimensional structural model—IV LASSO—employed in our study allows us to use the right sets of instruments and control variables in our estimation. This is a major contribution to the analysis of women's empowerment and gender wage gap on the methodological front.

2.3. The Ghanaian context

Ghana's population is currently estimated at around 31.07 million for 2020 with an annual growth rate of 2.2%. Of this, close to three-fifth dwell in urban areas and thus represents a huge increase in the extent of urbanisation in the country

compared to what pertained at the start of the millennium.[2] Regionally, much of Ghana's population dwell in the Greater Accra and Ashanti regions while the Upper West region has the least population. Two-thirds of Ghanaian households are headed by males and males are more likely to assume headship at an early age than females (GSS, 2018b). More than 48% of the population are aged between 15 and 49 years. This indicates the presence of a large youthful population in the country with implications for jobs and welfare.

Unlike the early 2000s wherein over half of the total employment in Ghana came from the agricultural sector, the agricultural sector's contribution to total employment stood at 33% in 2020, and thus has paved way for the service and industrial sectors to increase their contribution to total employment in the country (DTDA, 2020). For instance, the service sector accounts for 48% of total employment and the private informal sector employs 53% of the total employed labour force in the country. The latest wave of the GLSS suggests that about 65% of persons aged 15 years and older are employed in paid jobs in Ghana while close to 6% are unemployed. These aggregate indices however masque important variations across sex and locality. The incidence of unemployment is higher in urban areas (7.8%) than in rural areas (3.8%) while males are more likely to be employed in paid jobs compared to their female counterparts. There are also variations in these indices across regions in Ghana with the Greater Accra and Ashanti regions posting the highest proportions of unemployed persons. Of those employed, about 60% are own-account workers, while 26 and 9% are employees and contributing family workers, respectively. 6% are employers (DTDA, 2020). Persons aged 35 to 39 years have the highest labour force participation rate (LFPR) of around 92% while persons aged 15 to 19 years exhibit the lowest LFPR (35.4%). This reflects the fact that individuals within the 15 to 19 years age bracket are more likely to be in school compared to those in the 35 to 39 years age bracket. In terms of gender, the aged bracket with the highest LFPR is 35 to 39 years for males and 40 to 44 years for females.

Wage compensation from work in Ghana is low. Only 24% of urban employees are paid salaries that are higher than or at par with the national minimum wage of GHS11.82 (US$2.98)(see Anuwa-Amarh, 2016; Boahen and Opoku, 2021). Boahen and Opoku (2021) link this to the level of informality in Ghana with the informal sector accounting for around 90% of all the economic activities in the country and the difficulty that imposes on the enforcement of minimum wage laws as well as the inadequate nature of the labour law in Ghana when it comes to provisions on overtime payments. Gender gaps in paid employment and the remunerations thereof are prevalent in the country and this is mostly associated with cultural norms that determine the distribution of social roles. The prevailing patriarchal structure of some Ghanaian communities, notably, the systemic male domination and female subordination, social-cultural norms, restrict women's access to equal opportunities including paid employment and productive resources such as land. The limited access of women to paid employment often forces them to enter the labour market through self-employment with important implications on their ability to access productive employment opportunities. Also, the systemic cultural practices in some Ghanaian ethnic groups including denial of education, early marriages and the associated care responsibilities limit women's ability to play an active role in the labour market, thus exacerbating women's vulnerability to poverty. This differential access to labour market opportunities results in a situation where males obtain higher access to paid employment and better economic opportunities compared to their female counterparts. Even when men and women are assigned similar responsibilities at work, women receive 70% of the wages of their male counterparts (DTDA, 2020). The proportion of women engaged in non-agricultural self-employment with no employees is higher than that of men and less than a third of all indigenous firms in Ghana are owned by women.

In terms of welfare, the GSS (2018b) indicates that about a quarter of Ghanaians are poor (23.4% in 2016/17) whilst around 8.2% of the population are deemed to be extremely poor. This however varies across gender. For instance, female headed households have the lowest poverty incidence (17.6%) compared to their male counterparts (25.8%). While this presents a case that women might be doing better than men in terms of welfare, Oduro et al. (2011) observed that the value of the gross wealth of women is lower than those of men for all asset categories, making women more vulnerable to poverty than men.

3. Methodology and data

3.1. Methodology

Description of IV LASSO technique

The aim of many empirical research papers seeking to estimate causal or structural effects depends on using the right sets of instruments and controls to deal with unconfoundedness in the selection of unobservables and observables respectively. In this paper we use a machine learning method- the IV LASSO—which performs this model selection and inference that remain valid following model selection. The IV LASSO method used in this study offers an approach to estimate structural parameters in the presence of many potential instruments and controls based on techniques for estimating sparse high-dimensional models. In this case, this high-dimensional technique is used to select which instruments and control variables to use (see Belloni et al., 2012; 2014; Chernozhukov et al., 2015). The IV LASSO relies on an approximate sparsity assumption and the use of high-quality variable selection coupled with use of appropriate moment functions.

[2] See https://www.worldometers.info/demographics/ghana-demographics/

Using notations from Chernozhukov et al. (2015) (herewith CHS, 2015), in the ensuing presentation, we discuss the IV model, estimation approach and algorithms using the post regularization and Post Double Selection (PDS) methods by CHS (2015) and Belloni et al. (2014), respectively.

We consider a linear IV model

$$y_i = \alpha_0 d_i + x_i'\beta_0 + \varepsilon_i \tag{1}$$

$$d_i = x_i'\tau_0 + z_i'\delta_0 + u_i \tag{2}$$

with $E[(z_i', x_i')\prime\varepsilon_i] = E[(z_i', x_i')\prime u_i] = 0$. y_i represent the outcome variable (women's empowerment and welfare), d_i is the endogenous variable (gender wage gap) and α is the coefficient of interest, x_i is a p_n^x vector of exogenous control variable, z_i is a p_n^z vector of instruments, and n is the sample size. $p_n^x,\ p_n^z$ are a large set of intuitively chosen potential control variables and instruments from the literature.

We might have that z_i and x_i are correlated so that z_i are only valid instruments after accounting for x_i. Specifically, we let $z_i = \prod x_i + \zeta_i$, for $\prod$ is a $p_n^z \times p_n^x$ matrix and ζ_i is a p_n^z vector of unobservables with $E[x_i\ \zeta_i] = 0$. Substituting this expression for z_i as a function of x_i into (2) and then further substituting into (1) gives a system for y_i and d_i that depends only on x_i:

$$y_i = x_i'\theta_0 + \rho_i^y \tag{3}$$

$$d_i = x_i'\vartheta_0 + \rho_i^d \tag{4}$$

with $E[x_i\ \rho_i^y] = 0$ and $E[x_i\ \rho_i^d] = 0$. As indicated, our model allows for a large number of instruments and a large number of controls in our settings. Also, in order to estimate a baseline model without instruments- that is, accounting only for unconfoundedness in the selection of observables- we accommodate an exogenous case for d_i by setting $p_n^z = 0$ and imposing the additional condition $E[d_i\ \varepsilon_i] = 0$.

Following on, given that the dimensions of $\eta_0 = (\theta_0', \vartheta_0', \tau_0', \delta_0')'$ may be large or even larger than n (high dimensional parameter), informative estimation and inference about α_0 is impossible without imposing restrictions on η_0. An important approach and structure that has been used in the literature is approximate sparsity of the high-dimensional linear model. Approximate sparsity imposes a restriction that only S variables among all of variables $p_n^z,\ p_n^x$, where S is much smaller than n, have associated coefficients that are different from 0, while permitting a nonzero approximation error $r_{p,i}$. Therefore, estimators for this model attempt to learn the identities of the variables with large nonzero coefficients, while simultaneously estimating these coefficients. This approach allows the researcher to consider many variables and to use the data to learn which of the many variables are the most important. The setup also accommodates the case whereby the researcher does not know a priori exactly which suitable variables be it instruments or controls should be included in a model. Under the assumption of sparsity (see a detailed presentation of the generalization to approximate sparsity in Chernozhukov et al., 2015), we can assume that;

$$\|\eta_0\|_0 \leq S_n,\ S_n^2 \log\left(p_n^z + p_n^x\right)^3/n \ \to 0,$$

where $\|\eta_0\|_0$ is the l_0 'norm' of η_0 and denotes the number of non-zero components of η_0. In this case, sparsity requires that among the $p_n^z + p_n^x$ observed variables, the number of variables with non-zero coefficients is small relative to the sample size. The sparsity assumption then reduces the problem of estimating α_0 to a problem of finding which suitable instruments and controls to use in Eqs. (1) and (2). The bigger issue in doing this is the likelihood of making serious variable selection mistakes. For instance, a variable may be considered as relevant when in fact it has a zero coefficient and therefore has no true explanatory power, or a variable may be dropped from the model despite having a nonzero coefficient. Both kinds of errors may adversely affect post-model-selection estimators and inference for α. Whilst the spurious inclusion of irrelevant variables after being deemed predictive from looking at the data results in overfitting, the omission of relevant x variables leads to standard omitted variables bias. Again, when relevant z variables are excluded, one loses identification power. Albeit, the mistake stemming from the spurious inclusion of irrelevant variables, can be avoided through the use of modern, principled data-mining methods such as the LASSO[3] with appropriate tuning parameters (see Tibshirani, 1996; Belloni et al., 2012; Belloni et al., 2015, 2016),safeguarding against this type of mistake comes at the cost of needing to acknowledge that the omission of relevant variables is likely to occur. This is because while methods such as LASSO will correctly find strong predictors, it has been shown that such procedures have non-negligible probability of missing predictors with small but nonzero coefficients (see Chernozhukov et al., 2015). The omission of such predictors can have substantive impacts on inference for parameters of interest such as α in our model (see Leeb and Pötscher, 2008). The IV LASSO method used in this paper overcomes this difficulty by centring the estimation and inference on procedures that are robust to this type of model selection mistake. The approach in this paper relies on using estimating equations that are locally insensitive to these types of mistakes, termed orthogonal moment functions (see Belloni et al., 2015; Chernozhukov et al., 2015).

[3] LASSO or Lasso minimises the residual sum of squares subject to the sum of the absolute value of the coefficients being less than a constant.

In our IV model, such a moment condition is given by

$$M(\alpha_0 : \ \eta_0) = 0, \ M(\alpha, \eta) := \ E\left[\psi_i(\alpha, \eta)\right], \tag{5}$$

where $\psi_i(\alpha, \eta) = (\tilde{\rho}_i^y - \ \tilde{\rho}_i^d \alpha)\tilde{v}_{it}$ for $\eta := (\theta\prime, \vartheta\prime, \ \tau\prime, \delta\prime)$, $\tilde{\rho}_i^y := y_i - \ x_i'\theta$, $\tilde{\rho}_i^d := d_i - \ x_i'\vartheta$, and $\tilde{v}_i := x_i'\tau + z_i'\delta - \ x_i'\vartheta$. When we set $\eta = \eta_0$, we have $\tilde{\rho}_i^y = \rho_i^y = y_i - \ x_i'\theta_0$,

$$\tilde{\rho}_i^d = \rho_i^d \ = d_i - \ x_i'\vartheta_0 \text{and } \tilde{v}_i = v_i \ := \ x_i'\tau_0 + z_i'\delta_0 - x_i'\vartheta_0 = \zeta_i'\delta_0.$$

In this case, a small selection error will have relatively little impacts on the estimation of α_0 by noting that the following orthogonality condition holds:

$$\frac{\partial}{\partial \eta} M(\alpha_0, \ \eta)|_{\eta=\eta_0} = 0 \tag{6}$$

Put differently, missing the true value η_0 by a small amount does not invalidate the moments condition. Thus estimators $\hat{\alpha}$ of α_0 based on the empirical analogue of Eq. (5),

$$\hat{M}\left(\hat{\alpha}, \ \hat{\eta}\right) = 0 \tag{7}$$

with $\hat{M}(\alpha, \ \eta) := n^{-1}\sum_{i=1}^{n}[\psi_i(\alpha, \eta)]$, can be shown to be 'immunized' or 'orthogonalized' against small selection errors. A comprehensive general formulation of orthogonal moments functions for use in sparse high dimensional models and a number of estimation and inference results is presented in Belloni et al. (2013). It can be seen that operationally using the empirical version of Eq. (5) to estimate α_0 is equivalent to using the usual IV regression of ρ^y on ρ^d using v as instruments. Following from this, CHS (2015) suggest the following algorithm for estimating α_0 based on the 'double-selection' strategy of Belloni et al. (2014). Here, we first do Lasso or Post-Lasso regression of d_i on x_i, z_i to obtain $\hat{\tau}$ and $\hat{\delta}$. Then we do a Lasso or Post-Lasso regression of y_i on x_i to get θ. This is followed by another Lasso or Post-Lasso regression of $\widehat{d_i} = x_i'\hat{\tau} + z_i'\hat{\delta}$ on x_i to get ϑ. Letting $\hat{\rho}_i^y := y_i - \ x_i'\theta$, $\hat{\rho}_i^d := = d_i - \ x_i'\vartheta$ and $\hat{v}_i \ := \ x_i'\tau + z_i'\delta - x_i'\vartheta$, we retrieve estimator $\hat{\alpha}$ from Eq. (7) by using standard IV regression of $\hat{\rho}_i^y$ on $\hat{\rho}_i^d$ with $\hat{v}_i$ as the instruments. Inference is performed on α_0 using $\hat{\alpha}$ or the associated score statistic and conventional heteroscedasticity robust standard errors.

Again, we use the alternative algorithms following from the post double selection (PDS) strategy of Belloni et al. (2014) that would yield similar asymptotic properties. In this case, we follow the PDS strategy by running Lasso regression of $d_i$on x_i and z_i, followed by a Lasso regression of d_i on $x_{i,}$ and another Lasso regression of y_i on x_i. Then we form a 2SLS estimator using instruments selected in the first step and controlling for the union of controls selected in the three Lasso steps. The precise statement and proof of the properties of $\hat{\alpha}$ obtained from these algorithms can be found in Belloni et al. (2014) and Chernozhukov et al. (2015).

To ensure that relevant z variables are not excluded, we use the weak identification robust inference as in Belloni et al. (2012; 2013) and confidence sets based on Chernozhukov et al. (2013) super score weak identification robust tests. The super score test of statistical significance of the instruments is computed following the IV LASSO estimation. Here, the null hypothesis is that the coefficient on endogenous regressor d_i is $H_0 = b\ (d_i) = 0$. The rejection of the null indicates that the instruments are valid, that is orthogonal to the true disturbance (see Ahrens et al., 2018).

3.2. . Description and source of data

The study relied on the latest wave of the Ghana Living Standards Survey (GLSS) which was conducted by the GSS (see GSS, 2018a). The GLSS is a nationally representative repeated cross-sectional household surveys that contain information on a wide range of demographic and socio-economic factors, aggregated at both the individual and household levels. To date, seven rounds of the GLSS have been conducted with the first two waves occurring in 1987/88 and 1988/89 while the third, fourth, fifth and sixth waves conducted in 1991/1992, 1998/99, 2005/06 and 2012/13, respectively. The latest wave (i.e. GLSS 7) was conducted in 2016/17. The sampling design of the survey follows a two-stage stratified random sampling technique and thus results in two separate levels of aggregation – i.e. a primary sampling units (PSUs) and a secondary sampling units (SSUs). At the first stage, the PSUs (also called the census enumeration areas (EAs)) are allocated into the 10 administrative regions of Ghana using probability proportional to population size. The EAs are then disaggregated into urban and rural localities of residence. A complete listing of households in the selected EAs is done to form the SSUs. At the second stage, 15 households from each PSU are systematically selected. Thus, the final sampling unit for the survey is the population living in private households in Ghana. The GLSS 7 contains information on 59,864 individuals from 14,009 households in Ghana. Unlike the earlier rounds of the GLSS, wave 7 captures information on the main occupation as well as the ISIC sector of work. As a result, we were able to obtain detailed information on men's and women's jobs across sectors, industries, and occupations. This is very important as differences in jobs—whether across industries, sectors, and occupations—may primarily explain gender wage differences (see World Bank, 2012). We constructed all the set of variables employed in the empirical analysis using this cross-sectional dataset. In the ensuing paragraph, we discuss briefly how the main variables of interest were constructed.

Approach used in computing main variables

Following earlier studies in the literature, we computed the share of total household assets owned by female adult members of a household as a proxy for women's empowerment (see Doss, 2006, 2013; Allendorf, 2007; Friedemann-Sánchez and Lovatón, 2012; Oduro et al., 2015). The GLSS dataset contains information on the ownership of three main types of assets by members of a given household. We exploit this information to create three dummy variables with each representing whether or not a given type of asset is owned by someone within the household. The sum of these for each household yields a maximum value of 3 if all the three asset types are owned by at least one person within the household, regardless of sex. A gender-based measure is also derived mainly by taking the sum of these dummies and conditioning on the sex of the individual, per household. In the end, we obtain the female empowerment variable by expressing the latter measure as a share of the former measure.

Household welfare is attained by using the daily expenditure of the household per adult equivalent, regionally deflated, whereas women's welfare is the total household expenditure per adult equivalent for female-headed households.

In this paper, we follow the methodological approach used by OECD (2021) in the computation of gender wage gaps within households. Accordingly, we compute the gender gaps in earnings as the difference between the mean earnings of male and female adult household members relative to the mean earnings of male adult household members. Functionally, this is expressed as:

$$gap\_w = \frac{mean\_earnings_{male} - mean\_earnings_{female}}{mean\_earnings_{male}}$$

The computed mean gender wage gap within households is around 27%. This implies that for every 1 Ghanaian cedi equivalent earned by men within households, women earn 73 pesewas.[4]

The high-dimensional controls used in the study include variables that explain household gender wage gap as well as covariates that also explain the dependant variables as highlighted in the theoretical and empirical discussions. Following from the literature, we include several variables that portray household and family characteristics, human capital, occupation, ISIC sector of work, social norms and culture, formality, location, and household access to basic services and infrastructure (seeÑopo et al., 2011; World Bank, 2012; Langdon and Klomegah, 2013; Blau and Kahn, 2017; Sell and Minot, 2018). In all, we have 103 high-dimensional variables in our estimation. See Appendix Table A1 for description and summary statistics of all variables.

Choice and justification of instruments used in the IV-LASSO estimations

Since the estimates of the structural effect of gender wage gap within households on women's empowerment and welfare might be prone to reverse causality, we include a range of variables as potential instruments in the IV-LASSO model. With regards to the instruments, we choose a set of potential and well targeted good instruments from the literature to be selected upon. Under the exclusion restriction, the ideal set of chosen instruments using the IV LASSO provides a high-quality prediction of the endogenous variable— household gender wage gap. Using the IV LASSO with proper penalty parameters theoretically guarantees that any instruments selected are not simply spuriously correlated to the endogenous variable but have true predictive power. This means that IV LASSO could select no instruments at all as there may be no set of variables with sufficient predictive power to achieve the required standard. The potential instruments introduced following from the literature and the Ghanaian context are the presence and the number of children (disaggregated in various age cohorts) in households, an interaction between the presence of children aged 7 to 15 years in a household and ethnicity, a measure of whether the head of the household and his spouse work within the same sector of economic activity, the presence of aged dependants in a household and the presence of a disabled person in a household.

The presence of children below a certain age (say 6 years) within a household is expected to affect women's ability to participate actively in the labour market due to increased care responsibilities while the presence of children at certain ages (say, 7 to 15 years) may help relieve women of some domestic work including washing of dishes and cooking. The likelihood and extent of this is likely contingent on the culture of the individual or the household – this effect is capture by the interaction between the presence of children in the 7 to 15 age cohort and ethnicity. Also, the presence of aged and disabled persons within a household might mean greater care responsibility by women, thus lowering women's ability to take advantage of labour market opportunities as they would have to spend more time at home caring for such persons. Based on the observation that certain industries are traditionally dominated by women and others by men, Aizer (2010) relied on exogenous changes in the demand for labour in female dominated industries relative to that of males to purge potential endogeneity bias in the relationship between gender wage gap and violence. Following from this, we rely on a variable which captures information on whether heads of households and their spouses work within the same sector of economic activity as a plausible instrument for gender wage gap in this paper.

[4] 1 Ghanaian cedi=100 pesewas.

Table 1
Structural estimations for women's empowerment and household gender wage differences.

A: OLS using CHS (2015) lasso-orthogonalized vars		
Dep var: Women's empowerment	*Coeff*	*Robust std. error*
HH gender wage difference	−0.052***	0.003
B: OLS using CHS (2015) post-lasso-orthogonalized vars		
Dep var: Women's empowerment	*Coeff*	*Robust std. error*
HH gender wage difference	−0.047***	0.002
C: OLS with PDS-selected variables and full regressor set		
Dep var: Women's empowerment	*Coeff*	*Robust std. Error*
HH gender wage difference	−0.048***	0.002
Region (Volta)	0.264	0.058
Mother's education (tertiary)	−0.109	0.027
Age cohort (24–35 years)	−0.160	0.014
Occupation (craft and related workers)	0.156	0.078
Father's occupation (services)	0.032	0.008
Ethnicity (Dagomba)	0.108	0.037
Ethnicity (Ewe)	−0.101	0.019
ISIC sector of work (wholesale and retail)	−0.116	0.054
ISIC sector of work (social work)	−0.073	0.007
No access to electricity	0.033	0.019
Cons	0.357	0.016
Observ.	880	
No. of high-dim controls	103	
Selected controls	10	

Note: Robust SE and test statistics valid for only the *HH gender wage difference* variable. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

4. Discussion of empirical results

In this section, we discuss in detail the results of the structural effect of gender wage differences within households on women's empowerment as well as household and women's welfare. First, we discuss the findings for CHS (2015) and PDS (by Belloni et al., 2014) methods where we do not account for unconfoundedness in selection of unobservables, that is no instruments used followed by the IV LASSO approach where we introduce the instruments. Starting with the CHS (2015) where the Lasso-selected controls are used to construct orthogonalized versions of women's empowerment and welfare and our variable of interest–gender wage gap within households– we present the orthogonalized versions based on the Lasso and post Lasso estimated coefficients. The post Lasso is OLS applied to Lasso-selected variables, it is convenient to implement and works well in terms of convergence and bias compared to the Lasso (see Belloni and Chernozhukov, 2013; Belloni et al., 2012). In the CHS (2015) method, the selected high dimensional controls for women's empowerment and welfare, and gender wage gap are partialled out using the Lasso or post Lasso coefficient. All Lasso seclected controls for women's empowerment and welfare are found in Appendix A, Tables A2–A4. With respect to women's empowerment, in both Lasso and post Lasso, the structural parameters show that a reduction in the household gender wage gap significantly increases the share of household assets owned by women. (see Tables 1A and B).

Table 1C presents the PDS estimations on the effect of household gender wage difference on women's empowerment. Here, Lasso is used to select a set of variables that are useful for explaining women's empowerment, and a set of variables that are useful for explaining gender wage gap within households. We estimate the structural parameter α by OLS regression of women's empowerment on the gender wage gap and the union of the variables selected for explaining women's empowerment and gender wage gap. In this case, we use variables that are important for either of the two predictive relationships to guard against standard omitted variables bias when estimating α. The PDS method is equivalent to Frisch–Waugh– Lovell partialling out all selected controls, therefore we can draw inferences on the gender wage gap, but not on the selected high-dimensional controls. The estimated structural parameter of household gender wage difference using the PDS-selected variables and the full set of selected controls also shows the positive effect of reducing household gender wage gap on the share of household assets owned by women, and thereby women's empowerment. Specifically, a point decrease in the gender wage gap within households significantly boosts women's empowerment by 0.048 (see Table 1C). The findings seem consistent and connected to the literature on women's empowerment. The decline in gender wage gap within the household may enhance the decision-making roles of women, thereby strengthening their bargaining ability and empowering them within the household and community (see Doss 2006, 2013; Meier zu Selhausen 2016; Annan et al., 2020).

The structural estimates for the effect of household gender wage gap on household welfare are presented in Table 2. The structural parameters are consistent for OLS using the CHS (2015) Lasso and post Lasso orthogonalized variables and the PDS-selected variables and the full set of controls. The results indicate that a decline in household gender wage difference significantly improves household welfare. A point decrease in the gender wage gap within households results in a 5.3% increase in household welfare. In effect, the decrease in the gender wage gap provides better economic opportunities for

Table 2
Structural estimations for household welfare and household gender wage differences.

A: OLS using CHS (2015) lasso-orthogonalized vars		
Dep var: Log *Household welfare*	*Coeff*	*Robust std. error*
HH gender wage difference	−0.047***	0.005
B: OLS using CHS (2015) post-lasso-orthogonalized vars		
Dep var: Log *Household welfare*	*Coeff*	*Robust std. error*
HH gender wage difference	−0.048***	0.009
C: OLS with PDS-selected variables and full regressor set		
Dep var: Log *Household welfare*	*Coeff*	*Robust std. Error*
HH gender wage difference	−0.053***	0.007
Children <12 years	−0.026	0.006
Father's education (none)	0.031	0.036
Mother's education (none)	−0.155	0.046
Mother's education (secondary)	0.226	0.054
Mother's education (tertiary)	0.321	0.172
Father's occupation (Services)	0.176	0.014
Educational attainment (basic)	−0.122	0.006
Cooking fuel (wood)	−0.325	0.001
Cooking fuel (gas)	0.325	0.021
Time_drinking water	−0.001	0.001
Father's education (tertiary)	0.292	0.102
Religion (Islam)	0.025	0.154
Ethnicity (Ashanti)	0.188	0.097
Ethnicity (Nankasi)	−0.112	0.027
Occupation (skilled agriculture/fishery workers)	−0.067	0.024
Access to electricity	0.239	0.071
Cons	2.383	0.115
Observ	1709	
No. of high-dim controls	103	
Selected controls	16	

Note: Robust SE and test statistics valid for only the *HH gender wage difference* variable. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table 3
Structural estimations for women's welfare and household gender wage differences.

A: OLS using CHS (2015) lasso-orthogonalized vars		
Dep var: Log *women's welfare*	*Coeff*	*Robust std. error*
HH gender wage difference	−0.086***	0.019
B: OLS using CHS (2015) post-lasso-orthogonalized vars		
Dep var: Log *women's welfare*	*Coeff*	*Robust std. error*
HH gender wage difference	−0.099***	0.037
C: OLS with PDS-selected variables and full regressor set		
Dep var: Log *women's welfare*	*Coeff*	*Robust std. Error*
HH gender wage difference	−0.145***	0.075
Married	0.031	0.128
Region (northern)	−0.222	0.059
Father's education (tertiary)	0.355	0.005
Father's occupation (services)	0.118	0.066
Religion (Islam)	0.113	0.042
Religion (other)	−1.202	0.074
ISIC sector of work (professional and technical activities)	−0.099	0.037
Cooking fuel (wood)	−0.394	0.020
Cooking fuel (gas)	0.744	0.129
Cons	2.277	0.019
Observ.	295	
No. of high-dim controls	103	
Selected controls	12	

Note: Robust SE and test statistics valid for only the *HH gender wage difference* variable. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

both men and women in the household. This finding indicates that decreases in gender wage gap within households will contribute to poverty reduction (see Angel-Urdinola and Wodon, 2006).

With respect to the effect of household gender wage gap on women's welfare, the structural estimates show that decreases in the household gender wage gap result in significant increases in women's welfare (see Table 3). Here, we find that the effect on women's welfare is higher than that for the entire household welfare. Here again, the decrease in gender wage gap may enhance the ability of women to make independent decisions (such as investing in education, small enter-

Table 4
A: First-stage estimation(s):.

Dep var: HH gender wage difference	Coef.	Robust Std. Err.
Region (Volta)	−0.176	0.216
Mother's education (tertiary)	0.279**	0.115
Father's occupation (services)	0.066	0.057
Ethnicity (Dagomba)	−0.548	0.483
Ethnicity (Ewe)	−1.248**	0.563
Ethnicity (Nankansi)	0.201	0.230
Age cohort (24–35 years)	0.125	0.154
ISIC sector of work (wholesale and retail)	0.186***	0.071
ISIC sector of work (social work)	−0.650***	0.089
Occupation (services/sales workers)	0.222*	0.121
Occupation (craft and related workers)	−0.003	0.016
No access to electricity	−0.339*	0.203
Disability dependant	4.681***	0.572
Cons	0.064	0.041
Observ.	880	
Weak identification F stats, robust (Full set)	33.17	
B: IV using CHS(2015) lasso-orthogonalized vars		
Dep var: Women's empowerment	Coeff	Robust std. Error
HH gender wage difference	−0.007***	0.001
C: IV using CHS (2015) post-lasso-orthogonalized vars		
Dep var: Women's empowerment	Coeff	Robust std. Error
HH gender wage difference	−0.015***	0.001
D: IV with PDS-selected variables and full regressor set		
Dep var: Women's empowerment	Coeff	Robust std. Error
HH gender wage difference	−0.012***	0.002
Region (Volta)	0.275	0.050
Mother's education (tertiary)	−0.114	0.017
Father's occupation (services)	0.025	0.013
Ethnicity (Dagomba)	0.043	0.034
Ethnicity (Ewe)	−0.076	0.045
Ethnicity (Nankansi)	−0.150	0.033
Age cohort (24–35 years)	−0.161	0.019
ISIC sector of work (wholesale and retail)	−0.125	0.028
ISIC sector of work (social work)	−0.053	0.022
Occupation (services/sales workers)	0.004	0.027
Occupation (craft and related workers)	0.189	0.063
No access to electricity	0.058	0.012
Cons	0.379	0.071
Observ.	880	
No. of high-dim controls	103	
Selected controls	12	
Number of Instruments	8	
Selected instruments	1	

Note: Robust SE and test statistics valid for only the *HH gender wage difference* variable. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

prises, etc.) that may facilitate their access to better economic prospects (Doss, 2006; Doepke and Tertilt, 2011; Annan et al., 2020).

To help deal with the potential for simultaneity between household gender gap and women's empowerment and welfare, we introduce our set of 8 instruments and run the IV LASSO estimations using CHS (2015) and PDS methods. We begin the discussion by looking at the first stage estimations and the battery of weak identification tests. The first stage estimation is a Lasso regression of gender wage difference on the selected instruments and controls (see Table 4A). The Lasso selected instrument for the women's empowerment estimation is the presence of a disabled person in a household. The first-stage relationship shows that this variable after accounting for the Lasso selected control regressors is strongly correlated with the endogenous variable, therefore appears to be a strong instrument. The robust weak identification F statistics is very high for the IVs of the optimal Lasso and post-Lasso as well as the full IV set. We also reject the null hypothesis that the selected instrument is not valid or weakly identified for the Lasso and post Lasso orthogonalized based on the sup-score weak-identification-robust tests which are in effect high -dimensional versions of the Anderson -Rubin test.

We note that none of the instruments were selected using Lasso in the household and women's welfare estimations. This shows that the potential instruments have no sufficient predictive power to achieve the required standard and therefore the model is unidentified in this case. Thus, we rely on the earlier estimations without accounting for unconfoundedness in the unobservables and interpret the structural effect of the household gender wage gap on household and women's welfare not as a causal relationship.

Turning our attention to the IV LASSO regressions for women's empowerment, in the CHS (2015) estimations, the selected variables are again used to construct orthogonalized versions of our dependant variable (women's empowerment), endogenous (household gender wage gap) and control variables, and to create optimal instruments from the Lasso selected IV. The orthogonalized versions based on Lasso and post Lasso estimated coefficients using the optimal IV created for the endogenous regressor are presented in Tables 4B and C. Compared to the CHS (2015) estimates without using instruments, the OLS estimates using the CHS (2015) Lasso and post Lasso -orthogonalized versions seem to be biased upwards. The structural impact of a decline in household gender wage gap in both Lasso and post Lasso regressions significantly increase women's empowerment by 0.007 and 0.015 respectively.

In the PDS estimation, we use the Lasso selected controls and instrument in a post regularization IV estimation. As indicated, we form a 2SLS estimator using the selected instrument for the household gender wage gap with the union of selected high-dimensional controls for both women's empowerment and household gender wage gap as controls variables. The results for the structural parameter α using IV with PDS-selected variables and full regressor set are consistent with CHS (2015) estimates (see Table 4D).

5. Conclusions and policy implications

In this paper, we explain the effect of gender wage differences within households on women's empowerment, household welfare, as well as women's welfare using the latest wave of a micro household dataset from Ghana. Given the many issues fraught with econometric estimation with respect to model selection, we use the IV LASSO, a machine learning technique, to carry out the estimations in this study. The findings of the estimations for the structural parameter—gender wage gap—show that a reduction in household gender wage gap have a substantially and positive impact on women's empowerment. Similarly, decreases in household gender wage gap result in a significant increase in household and women's welfare. The increasing effect on the welfare of women stemming from a decrease in household gender wage differences within household is greater than that of total household welfare.

These findings speak greatly to the literature on how gender gaps shape development outcomes at the household level. The context of the study—Ghana—is also insightful as such empirical studies on SSA are notably lacking. Largely, the decline in gender wage gap within the household may empower women by improving their decision-making roles and therefore bolstering their bargaining power within the household. Some of these decisions may augment the ability of women to make independent decisions that are beneficial to their well-being. For instance, women may choose to invest in education or set up small enterprises to boost their incomes. Also, the decrease in gender wage gap may facilitate the entry of both men and women to better and sustainable economic possibilities.

The analysis indicates the need for policy to narrow the male-female wage gap. Given the evidence of lower poverty incidence in female headed households, improved pay parity may be a path to eradicate extreme poverty in developing countries. Along this line, the analysis indicates the significance of addressing women's constraints to accessing decent work-through policies and strategies that expand the choices of women and remove the barriers they face in the quest to work. Initiatives under such projects may include well-designed skills development programmes that equally meet the differing demands of men and women, increase access to child care for women, encouraging uptake of shared parental leave and other gender pay gap narrowing policies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A1, Table A2, Table A3, Table A4.

Table A1
Description of regression variables and summary statistics.

Variable	Description	Mean	SD	Range
HH gender wage gap	Continuous: measures gender gaps in earnings within households	−0.269	5.437	−99–0.964
Women's empowerment	Continuous: measures female empowerment and it is computed as the share of total household assets owned by female adult members of the household	0.437	0.379	0–1
Women's welfare	Continuous: captures the total household expenditure per adult equivalent for female-headed households	10.499	9.879	0.259–245.676
HH welfare	Continuous: captures the daily expenditure of the household per adult equivalent, regionally deflated	9.144	9.841	0.107–546.967
Investment in girl child	Continuous: captures the total amount of expenditure incurred by households towards the schooling of girls aged below 18 years	1073.234	2054.17	0–62,220
HH size	Continuous: captures the total number of members of the household	6.276	3.622	1–31
Nationality status	Binary: captures the nationality status of the respondent; it assumes a value of 1 if non-Ghanaian and zero otherwise	0.015	0.122	0–1
Religion	Categorical: measures the religious affiliation of the respondent; it consists of five distinct categories with the following values and associated labels: 0 if 'No religion', 1 if 'Christian', 2 if 'Islam', 3 if 'Traditionalist', and 4 if 'Other'	1.306	0.638	0–4
Ethnicity	Categorical: measures the ethnic group of the respondent; it consists of nine distinct categories with the following values and associated labels: 0 if 'Fante', 1 if 'Dagomba', 2 if 'Nzema', 3 if 'Asante', 4 if 'Nankansi', 5 if 'Dagarte', 6 if 'Ewe', 7 if 'Ga', and 8 if 'Other'	5.571	2.799	0–8
Sex	Binary: measures the gender of the individual; it assumes a value of 1 if 'male' and 0 otherwise.	0.484	0.500	0–1
Age cohort	Categorical: measures the age cohort of the individual; this includes five distinct age groups, namely, '15–24 years cohort', '25–34 years cohort', '35–44 years cohort', '45–54 years cohort', and '55–64 years cohort'	1.375	1.329	0–4
Father's education	Categorical: measures the highest educational attainment of the individual's father; it assumes a value of 0 if 'None', 1 if 'Basic', 2 if 'Secondary', 3 if 'Tertiary', and 4 if 'Do not Know'	0.948	1.247	0–4
Mother's education	Categorical: measures the highest educational attainment of the individual's mother; it assumes a value of 0 if 'None', 1 if 'Basic', 2 if 'Secondary', 3 if 'Tertiary', and 4 if 'Do not Know'	0.514	0.994	0–4
Educational attainment	Categorical: measures the highest educational attainment of the individual. It assumes a value of 0 if 'None', 1 if 'Basic', 2 if 'Secondary', 3 if 'Tertiary' and 4 if 'Do not Know'.	1.348	0.648	0–4
Father's occupation	Categorical: measures the occupation of the individual's father; it assumes a value of 0 if 'Agriculture', 1 if 'Industry/Manufacture', 2 if 'Services', 3 if 'Other', and 4 if 'Do not Know'	0.763	1.069	0–4
Mother's occupation	Categorical: measures the occupation of the individual's mother; it assumes a value of 0 if 'Agriculture', 1 if 'Industry/Manufacture', 2 if 'Services', 3 if 'Other', and 4 if 'Do not Know'	0.820	1.030	0–4
Region	Categorical: measures the region of residence of the individual; it assumes a value of 1 if 'Western', 2 if 'Central', 3 if 'Greater Accra', 4 if 'Volta', 5 if 'Eastern', 6 if 'Ashanti', 7 if 'Brong Ahafo', 8 if 'Northern', 9 if 'Upper East', and 10 if 'Upper West'	5.891	2.890	1–10
Urban	Binary: measures the locality of the individual; it assumes a value of 1 if 'urban' and 0 otherwise	0.363	0.481	0–1
Married	Binary: measures the marital status of the individual; it assumes a value of 1 if 'married'	0.263	0.440	0–1
Children <6 years	Continuous: captures the number of household members aged below 6 years	1.046	1.150	0–11
Children 6–12 years	Continuous: captures the number of household members aged between 6 and 12 years	1.354	1.362	0–10
Children <11 years	Continuous: captures the number of household members aged between 6 and 12 years	2.018	1.829	0–16
Children 7–15 years	Continuous: captures the number of household members aged between 7 and 15 years	1.686	1.614	0–13
Boys 7–15 years	Continuous: captures the number of male household members aged between 7 and 15 years	0.870	1.061	0–7
Girls 7–15 years	Continuous: captures the number of female household members aged between 7 and 15 years	0.816	1.016	0–8
Child_ethnicity	Continuous: captures the interaction of the number of household members aged between 7 and 15 years and ethnicity	4.100	3.461	0–8
Same_sector	Binary: measures whether the head and his/her spouse work within the same economic sector; it assumes a value of 1 if 'yes' and zero otherwise	0.746	0.435	0–1
Disability_dep	Binary: measures whether a household has a disabled person; it assumes a value of 1 if 'yes' and zero otherwise	0.012	0.109	0–1
Aged_dependant	Binary: measures whether a household has a member older than 60 years and not working; it assumes a value of 1 if 'yes' and zero otherwise	0.024	0.153	0–1

(*continued on next page*)

Table A1 (*continued*)

Public	Binary: measures the sector of employment of the individual; it assumes a value of 1 if 'employed in the public sector' and 0 otherwise	0.051	0.219	0–1
Phone	Binary: measures whether at least one individual owns a cell phone within the household; equal to 1 if yes	0.990	0.101	0–1
Receipt of remittance	Binary: measures whether any member of the household received remittances; equal to 1 if yes	0.046	0.210	0–1
Migrant in HH	Binary: measures whether a household has an out-migrant; equal to 1 if yes	0.071	0.256	0–1
Health	Binary: measures whether the individual consulted a health practitioner in the past two weeks; equal to 1 if yes	0.086	0.280	0–1
Sick	Binary: measures whether the individual reports being sick in the past two weeks; equal to 1 if yes	0.133	0.339	0–1
Formality	Binary: measures whether the individual is employed in the formal sector; equal to 1 if yes	0.178	0.383	0–1
Sex of head	Binary: measures the gender of the household head; it assumes a value of 1 if 'male' and 0 otherwise	0.747	0.435	0–1
Non-poor	Binary: measures the poverty status of the household; it assumes a value of 1 if 'not poor' and 0 otherwise	0.636	0.481	0–1
Distance to get drinking water	Continuous: measures the time (in minutes) taken to get drinking water and back	6.738	3.736	1–16
Distance to get general water	Continuous: measures the time (in minutes) taken to get to general use water and back	5.967	3.952	1–16
Type of dwelling	Categorical: captures the type of dwelling used by the individual; it assumes a value of 1 if 'Separate house', 2 if 'Semi-detached house', 3 if 'Flat/Apartment', 4 if 'Compound house (rooms)', 5 if 'Huts/Buildings (same compound)', 6 if 'Huts/Buildings (different compound)', 7 if 'Tent', 8 if 'Improvised home (kiosk/container, etc.)', 9 if 'Living quarters attached to office/shop', 10 if 'Uncompleted building', and 11 if 'Other'	3.211	1.600	1–11
Number of rooms	Continuous: captures the number of rooms in the household	2.780	1.978	1–33
Number of sleeping rooms	Continuous: captures the number of sleeping rooms in the household	2.368	1.584	1–16
Main source of electricity	Categorical: captures the main source of electricity used by the household; it assumes a value of 1 if 'National grid connection', 2 if 'Local mini grid', 3 if 'Private generator', 4 if 'Solar home system', 5 if 'Solar lantern/Lighting system', 6 if 'Rechargeable battery', 7 if 'Other', and 8 if 'No electric power'	3.142	3.171	1–8
Main source of cooking fuel	Categorical: captures the main source of fuel used by the household; it assumes a value of 1 if 'None, no cooking', 2 if 'Wood', 3 if 'Charcoal', 4 if 'Gas', 5 if 'Electricity', 6 if 'Kerosene', 7 if 'Crop residue', 8 if 'Sawdust', 9 if 'Animal waste', and 10 if 'Other'	2.609	0.986	1–10
ISCO_work	Categorical: captures the category of work done by the individual; it assumes a value of 0 if 'Armed forces', 1 if 'Managers' 2 if 'Professionals' 3 if 'Technicians and associate professionals', 4 if 'Clerical support workers', 5 if 'Service and sales workers', 6 if 'Skilled agricultural, forestry and fishery workers', 7 if 'Craft and related trades workers', 8 if 'Plant and machine operators, and assemblers', and 9 if 'Elementary occupations'	5.612	1.400	0–9
ISIC_work	Categorical: captures the primary sector within which the individual is employed; it assumes a value of 1 if 'Agriculture, forestry and fishing', 2 if 'Mining and quarrying', 3 if 'Manufacturing', 4 if 'Electricity, gas, stream and air conditioning supply', 5 if 'Construction', 6 if 'Wholesale and retail; repair of motor vehicles and motorcycles', 7 if 'Transportation and storage', 8 if 'Accommodation and food service activities', 9 if 'Information and communication', 10 if 'Financial and insurance activities', 11 if 'Real estate activities', 12 if 'Professional, scientific and technical activities', 13 if 'Administrative and support service activities', 14 if 'Public administration and defence; compulsory social security', 15 if 'Education', 16 if 'Human health and social work activities', 17 if 'Arts, entertainment and recreation', 18 if 'Other service activities', and 19 if 'Activities of extraterritorial organisations and bodies'	4.805	5.652	1–19
Main occupation	Categorical: captures the type of work done by the individual; it assumes a value of 1 if 'Legislators/managers', 2 if 'Professionals', 3 if 'Technicians and associate professionals', 4 if 'Clerical support workers', 5 if 'Service/sales workers', 6 if 'Skilled agriculture/fishery workers', 7 if 'Craft and related trades workers', 8 if 'Plant machine operators and assemblers', 9 if 'Elementary occupations', and 10 if 'Other occupations'	5.881	1.399	1–10

Source: authors' compilation based on GLSS 7.

Table A2
LASSO estimations for women's empowerment and household gender wage differences.

Selected controls	LASSO	Post-estimation OLS
PDS LASSO Step 1—*y* (share of household assets owned by women)		
Region (Volta)	0.051	0.163
Mother's education (tertiary)	−0.075	−0.166
Ethnicity (Dagomba)	0.019	0.013
Age cohort (24–35 years)	−0.126	−0.169
Occupation (craft and related workers)	0.102	0.172
PDS LASSO step2—*d* (household gender wage difference)		
Father's occupation (services)	0.058	0.067
Ethnicity (Dagomba)	0.121	0.285
Ethnicity (Ewe)	0.044	0.082
ISIC sector of work (wholesale and retail)	0.300	0.379
ISIC sector of work (social work)	−0.133	−0.825
No access to electricity	−0.272	−0.564

Note: OLS, ordinary least square; PDS, post-double selection.

Table A3
LASSO estimations for household welfare and gender wage differences.

Selected controls	LASSO	Post-estimation OLS
PDS LASSO Step 1—*y* (household welfare)		
Children <12 years	−0.031	−0.016
Father's education (none)	−0.095	−0.020
Mother's education (none)	−0.143	−0.216
Mother's education (secondary)	0.132	0.169
Mother's education (tertiary)	0.418	0.446
Father's occupation (services)	0.015	0.210
Ethnicity (Nankasi)	−0.163	−0.066
Educational attainment (basic)	−0.187	−0.152
Cooking fuel (wood)	−0.436	−0.298
Cooking fuel (gas)	0.023	0.316
PDS LASSO Step 2—*d* (household gender wage difference)		
Time_drinking water	0.001	0.001
Father's education (tertiary)	0.046	−0.019
Father's occupation (services)	0.039	0.023
Religion (Islam)	0.208	0.162
Ethnicity (Ashanti)	0.104	0.091
Ethnicity (Nankasi)	−0.214	−1.308
Occupation (skilled agriculture/fishery workers)	−0.084	−0.242
Access to electricity	0.052	0.109
Cooking fuel (gas)	0.037	0.267

Table A4
LASSO estimations for women's welfare and gender wage differences.

Selected controls	LASSO	Post-estimation OLS
PDS LASSO Step 1—*y* (women's welfare)		
Married	0.235	0.261
Father's education (tertiary)	0.267	0.259
Religion (Islam)	0.017	0.044
Religion (Other)	−1.236	−1.269
Cooking fuel (wood)	−0.190	−0.308
Cooking fuel (gas)	0.571	0.612
PDS LASSO Step 2—*d* (household gender wage difference)		
Married	−0.468	−0.724
Region (northern)	0.142	0.825
Father's occupation (services)	0.018	0.187
Religion (Islam)	0.511	(Omitted)
Ethnicity (Dagomba)	0.002	(Omitted)
ISIC sector of work (professional and technical activities)	0.088	0.321

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